Modeling Spatial Organization with Swarm Intelligence Processes

Rawan Ghnemat[1,*] and Cyrille Bertelle[1] and Gérard H.E. Duchamp[2]

[1]LITIS, University of Le Havre, 25 rue Philippe Lebon, B.P. 540, 76058 Le Havre cedex, France
[2]LIPN, University of Paris XIII, 99 avenue Jean-Baptiste Clément, 93430 Villetaneuse, France
[*]Corresponding authors

Abstract: Urban Dynamics modeling needs to implement spatial organization emergence in order to describe the development of services evolution and their usage within spatial centers. In this paper, we propose an extension of the nest building algorithm with multi-center, multi-criteria and adaptive processes. We combine a decentralized approach based on emergent clustering mixed with spatial constraints or attractions. Typically, this model is suitable to analyse and simulate urban dynamics like the evolution of cultural equipment in urban area.

Keywords: Swarm intelligence; complex systems; self-organization; ant systems; spatial organization.

1 Introduction: From Urban Dynamics to Complex Systems

Urban systems have emergent properties based on their spatial development. This spatial development is both the result of some mecanisms from the system behavior and the actor of the system formation by morphogenetic feedback. The goal of this paper is to study some computable mecanisms and algorithms able to model such spatial self-organization processes, taking into account the complexity of the phenomena.

Complex system theory (Le Moigne, 1999) is based on the fact that, for many applicative domains, we can find similar processes linking emergent global behavior and interaction network of constituents. The global behavior is generally not accessible using classical analytical methods.

In classical analytical methods, the global behavior of the system is the description of the equations. Simulations from these formulations consist in obtaining the trajectories of the behavior predefined by the equations.

In complex systems modeling, we have to model the constituents of the system and the interaction network or system which links these constiuents, using a decentralized approach. So the global behavior of the system cannot be understood by the description of each constituent. In complex system modeling, the global

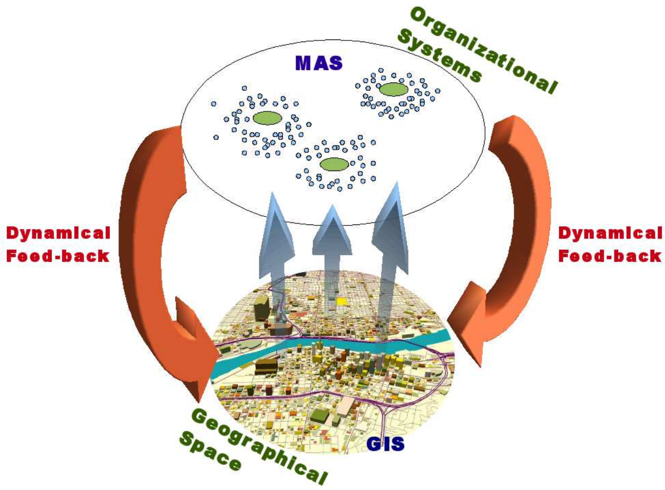


Figure 1 Complexity of geographical space with respect of emergent organizations

behavior is an emergent property from the interaction network or systems between its constituents which leads to the creation of a dynamical organization of these constituents.

This dynamical and emergent organization retro-acts on its own components. Two kinds of feedbacks allow to describe these phenomenon. The positive feedback means that the emergence increases the organization constitution. the negative feedback means that the emergence has regulator properties which will finally stop the increasing organization constitution and allow the system stabilization.

Another major aspect of complex systems is that they can be considered as open systems. This means that they are crossed by energetical fluxes that make them evolve in a continuous way. From these energetical fluxes, complex systems can evolve through critical states, using bifurcation schema and attractors behaviors. One of the major vector or support of these energetical fluxes is the environment itself where the complex systems and their entities evolve. In many natural and artificial systems, the environement has some spatial effects which interact on the whole complexity of the phenomenon. This spatial environment can be modified by the system but he can also be the catalyst of its own evolution. Understanding and modelling the deep structural effect of the interaction between the systems and its spatial environment is the goal of the study presented in the sequel.

Social and human developments are typical complex systems. Urban development and dynamics are the perfect illustration of systems where spatial emergence, self-organization and structural interaction between the system and its components occur. In figure 1, we concentrate on the emergence of organized systems from geographical systems. The continuous dynamic development of the organization feed-back on the geographical system which contains the organization components and their environment. To analyse or simulate urban dynamics, nowadays, we can use the great amount of geographical databases directly available for computational treatment within Geographical Information Systems. On the organizational level description, the new development of multiagent systems (MAS) allows nowadays to develop suitable models and efficient simulations.

The applications we focuss on in the models that we will propose in the following concerns specifically the multi-center (or multi-organizational) phenomona inside urban development. As an artificial ecosystem, the city development has to deal with many challenges, specifically for sustainable development, mixing economical, social and environmental aspects. The decentralized methodology proposed in the following allows to deal with multi-criteria problems, leading to propose a decision making assistance, based on simulation analysis.

Gentrification phenomena can be modelled using such methodology. It is typically a multi-criteria self-organization processes where appears emergent coming of new population inside urban or territorial areas. This new population firstly attracted by some criteria, brings some other charateristics which are able to modify and feedback over the environment.

Cultural dynamics processes in urban areas are also such complex systems where multi-criteria must be taken into account. A modelling of these dynamics is presented later in this paper.

2 Swarm Intelligence for Spatial self-Organization

Decentralized algorithms have been implemented for many years for various purposes. In this family of algorithms, multi-agent systems can be considered as generic methods (Weiss, 1999). Agent-based programming deals with two main categories of agent concepts: cognitive agents and reactive agents. The first category concerns sophisticated entities able to integrate, for example, knowledge bases or communications systems. Generally, efficient computations, based on these cognitive architectures, implement few agents. The second category of agents, based on reactive architectures, is expected to be used inside numerous entity-based systems. The aim of programs using such architectures, is to deal with emergent organizations using specific algorithms called emergent computing algorithms. Swarm Intelligence is the terminology used to point out such reactive agent-based methods where each entity is built with the same basis of behavior, but reacts in autonomous way. Swarm Optimization methods concern the problems of optimization where the computation of a function extremum is based on the concept of swarm intelligence.

Ant Colony Optimization (ACO) methods (Bonabeau et al., 1999) is a bioinpired method family where the basic entities are virtual ants which cooperate to find the solution of graph-based problems, like network routing problems, for example. Using indirect communications, based on pheromon deposites over the environment (here a graph), the virtual ants react in an elementary way by a probabilistic choice of path weighted with two coefficients, one comes from the problem heuristic and the other represent the pheromon rate deposit by all the ants until now. The feed-back process of the whole system over the entities is modelled by the pheromon action on the ants themselves.

Particule Swarm Optimization (PSO) is a metaheuristic method initially proposed by J. Kennedy and R. Ebenhart (Kennedy and Eberhart, 1995).This method is initialized with a virtual particle set which can move over the space of solutions corresponding to a specific optimization problem. The method can be considered as an extension of a bird flocking model, like the BOIDS simulation from C.W. Reynolds (Reynolds, 1987). In PSO algorithm, each virtual particle moves according to its current velocity, its best previous position and the best position obtained from the particles of its neighborhood. The feed-back process of the whole system over the entities is modelled by the storage of this two best positions as the result of communications between the system entities.

Other swarm optimization methods have been developped like Artificial Immune Systems (De Castro and Timmis, 2002) which is based on the metaphor of immune system as a collective intelligence process. F. Schweitzer proposes also a generic method based on distributed agents, using approaches of statistical many-particle physics (Schweitzer, 2003).

The method proposed in this paper is based on Ant Clustering and Ant Nest Building, allowing to deal with self-organization processes emerging from spatial constraints and attractive areas.

2.1 Ant Custering Modeling

Ant clustering algorithms are inspired by the corposes or larvea classification and aggregation that the ants colony are able to do in the real life. The ants are moving inside a closed area and are able to move some material which are randomly put on this area. After a while, and without any kind of centralized coordonation, the ants success to create some material clusters.

The algorithm is based on the following and very simple behavioral rules that each ant implements:

- When an ant is moving without carrying yet material and finds some material, the ant will take the material w.r.t. the probability number:

$$P_p = \left(\frac{k_1}{k_1 + f}\right)^2 \tag{1}$$

  where f is the material density that the ant perceives locally around itself and k_1 is the treshold. It is easy to check that if $f << k_1$ then P_p is near the value 1 and if $f >> k_1$ then P_p is near the value 0.

- When an ant is moving when carrying some material, the probability to deposit reads:

$$P_d = \left(\frac{f}{k_2 + f}\right)^2 \tag{2}$$

  where f is still the material density that the ant perceives locally around itself and k_2 is another treshold. It is easy to check that if $f << k_2$ then P_d is near the value 0 and if $f >> k_2$ then P_d is near the value 1.

2.2 Spatial constraints using templates

The ant clustering shows some spatial self-organizations but has the specificity of generating clusters at random places. According to the first random move that the ants start to do at the beginning of the algorithm, some material will initiate aggregation and the clustering processus will complete this aggregation from these initial random first aggregations. To simulate some urban dynamics, we need to introduce specific location with respect to city center for example or cultural equipments. The clustering here will represent the people usage of these centers or equipments and we need to introduce an attractive effect by using a pheromon template. This method follows the algorithm known as Ant Nest Building (Bonabeau et al., 1999). In ant colonies, the center corresponds to the position of the queen which needs to build the nest and the ant colony moves around it to protect the nest by various material taken on the ground. The queen emits a pheromon which allows to attract the ants during their building. The ant has to deposit the material carried only if the pheromon quantity perceived belongs to a specific range. We use an attractive fonction called P_t, corresponding to a pheromon template and represented by the left top part of the figure 2.

Using this template function, we remplace in the clustering algorithm, the two previous probabilities defined in equation (1) and equation (2) by

$$P'_p = P_p(1 - P_t) \tag{3}$$

$$P'_d = P_d P_t \tag{4}$$

In figure 2, we show an implementation of this algorithm using the multi-agent platform called Repast (Repast web site, 2009). The java version of this platform includes some packages allowing to interface with geographical database and geographical information systems (GIS). In figure 2, the graphical output windows is made under OpenMap which is a GIS developped in Java. In this figure, the materials moved by the ants are the small grey or blue circles, the ant moving without material are the green circles and the ant carrying material are the red circles.

2.3 Adaptive Spatial Organization Feedback Implementation

Complex systems deal not only with emergent organization processus from the interaction of its own entities, but also with the feedback processus of the organization over its own components. In the proposed model, we can take into account such feedback process and we present, in figure 3, an adaptive processus which makes the queen (which describes the organization itself) modify the environment and the clustering processus itself. Following the template function, the queen locally defines around it two zones. The first zone is near itself and it is expected not to find material there. The second zone corresponds to the template maximum and it is expected to find a great concentration of material there. In the simulation, we count in a dynamic way the number of materials in these two zones and when these numbers reach some tresholds, we make evolve the queen by increasing its own size and so increasing the 2 associated zones. After this evolution, the ants have to move some material following the new template function attraction. The low part of the figure shows the evolution of the queen which has evolved 6 times

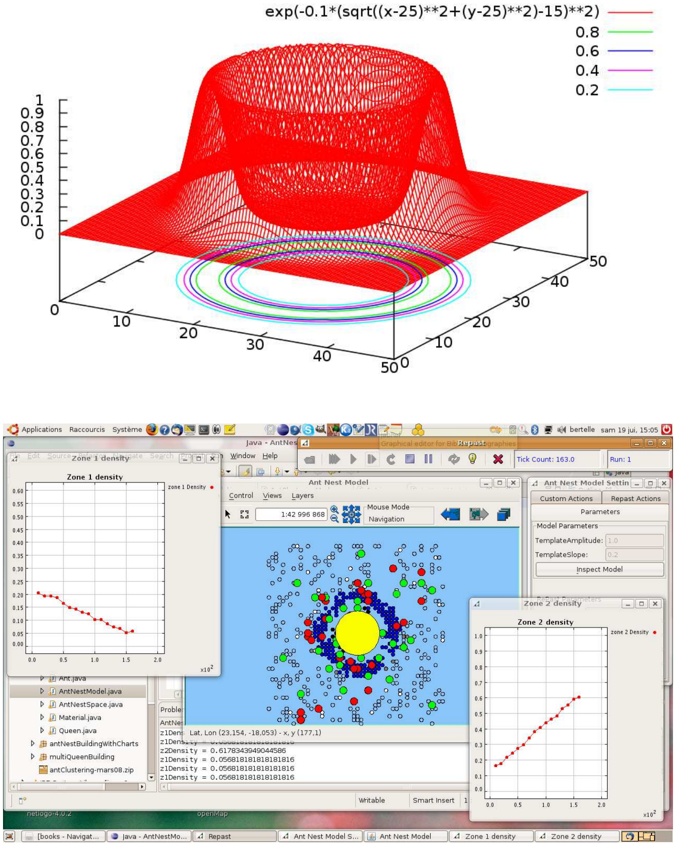


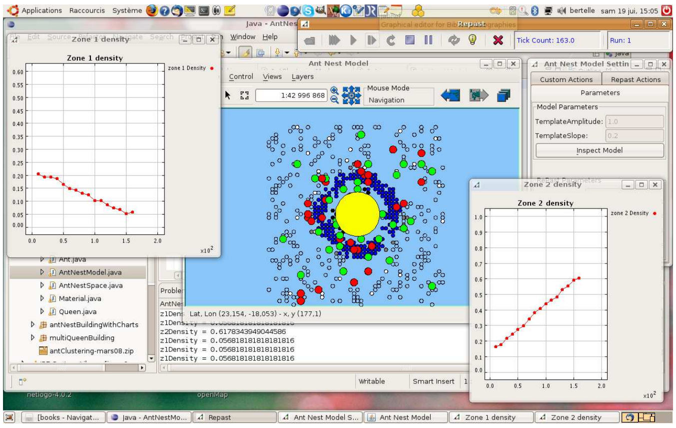
Figure 2 Templates and associated Ant Nest Building Simulation

since the simulation beginning. On this figure, we can see the red curves counting the zones density. Each gap in these density curves corresponds to an evolution of the queen.

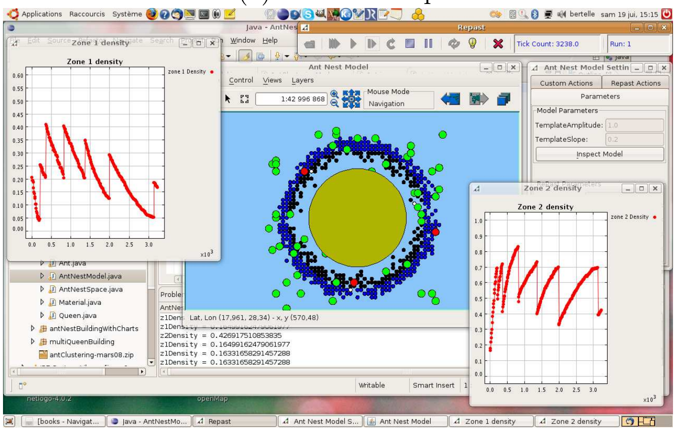
3 Multi-Criteria and Multi-Center System Dynamics

The swarm intelligence algorithms described in the previous section, are the direct formalization of natural social insects systems. They can be considered as the first stage of our modeling organization. From these *elementary models*, we propose to combine different elements and we need to add other processes in order to model more sophisticated phenomena, by the integration of the following aspects: multi-center, multi-criteria and adaptivity extension for multi-criteria.

To introduce the concept of multi-criteria phenomena, we introduce different kinds of pheromones. Each kind of pheromone is represented by a specific color. We introduce the notion of center which is a specific spatial location. On each center, we are able to define many queens. Each queen, belonging to a center,



(a) after few step



(b) after queen adaptive development

Figure 3 Adaptive queen behavior modelling: according to its surround material spatial perception, the queen evolves

is able to emit its own pheromone which is represented by a colored pheromone that is different from the other queen ones belonging to the same center. A queen, associated to a spatial center, describes a specific criterium linked to a colored pheromone. To represent the same criterium on different centers, we describe it by the same colored pheromone on these different spatial locations.

In order to force the ants to deposit their material only near the center, we have introduced the template function. Even if the pheromone function and the template function must have similarities in order to attract and make deposit the material at the same place, we have to separate these two functions. The template function must exhibit a close area of non nul values near the center to link the material to the center. The pheromone function must attract ants with material on the same place but the attraction phenomena has to cover a widest area than the template function, in order to be able to attract materials and ants at some distance from the center.

Definition 3.1 *A spatial multi-criteria multi-center simulation is described by a*

set of n_p ***centers****, $\{P_i; 1 \leq i \leq n_p\}$, and by a set of n_c* ***colors****, $\{c_j; 1 \leq j \leq n_c\}$.*
*For each center P_i, we define a c_j**-colored template function**, $\Phi_{ij} : S \to I\!R$, which gives the value of the c_j template intensity on each spatial position.*
*For each center P_i, we can define a c_j**-colored pheromone function**, $f_{ij} : S \to I\!R$, which gives the value of the c_j pheromone intensity on each spatial position.*

Remark 3.2 *We can define the c_j-colored template function of the P_i center by the following* **radial exponential function**

$$\Phi_{ij}(x, y) = \alpha_{ij} \exp(-\beta_{ij}(d((x, y), (x_{P_i}, y_{P_i})) - r_{ij})^2) \tag{5}$$

where α_{ij} is the template amplitude, β_{ij} is the template slope, (x_{P_i}, y_{P_i}) are the P_i center coordinates.
We then define the c_j-colored pheromone function for the P_i center with a similar formula

$$f_{ij}(x, y) = a_{ij} \exp(-b_{ij}(d((x, y), (x_{P_i}, y_{P_i})) - r_{ij})^2) \tag{6}$$

where a_{ij} is the template amplitude, b_{ij} is the template slope.

We have to remark that the radius r_{ij} is the same in the above two formulas and allows to define the same maximum value position, but the amplitude and slope are differents. The slope of template function has to create close area of maximal value near the center. The slope of the pheromone function must not have maximal area too much close to the center in order to attract ants or materials which are located at some distance from the center.

Figure 4 represents two centers and two colored pheromons. The template function used to represent the pheromone emission corresponds to the function defined in the remark 3.2. On the bottom of the figure, we present the associated simulation in Repast.

We give in the following some definitions which allow to generalize the ant nest building algorithm for the multi-criteria multi-center simulation.

Definition 3.3 *A center P_i has the* ***dominant color*** *c_j if*

$$a_{ij} = \max\{a_{ik}; 1 \leq k \leq n_c\}.$$

Definition 3.4 *On each space location $Z = (x, y)$, we define the c_j* ***colored pheromone intensity*** *as the function $F_j(Z)$ or $F_j(x, y)$ defined by the formula:*

$$F_j(Z) = F_j(x, y) = \sum_{i=1}^{n_p} f_{ij}(x, y). \tag{7}$$

The multi-criteria multi-center model proposed here, implement some spatial objects that are the material and spatial agents (which are the ants). The ants have to carry the material in order to achieve the spatial self-organization simulation.

Definition 3.5 *A material involved in a spatial multi-criteria multi-center simulation has to include a* ***characteristic color table*** *which corresponds to the only colors that the material is able to perceive and upon which it will be able to react.*

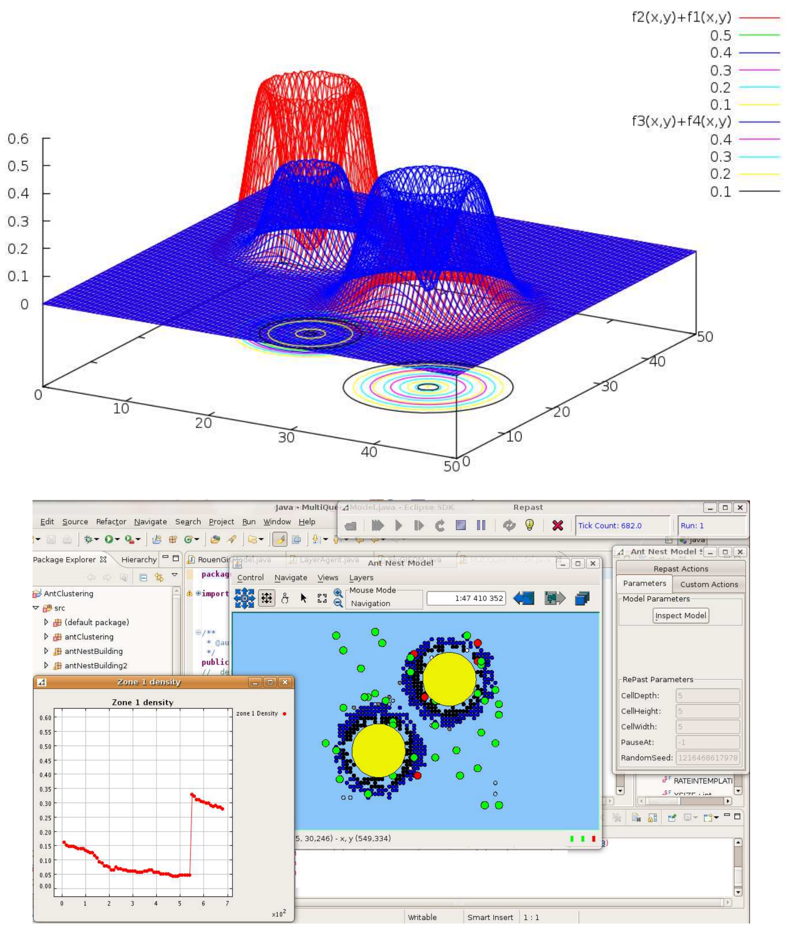


Figure 4 Multi-center multi-colored pheromone template represented by radial exponential functions and the associated ant nest building simulation in Repast

Definition 3.6 *An ant involved in a spatial multi-criteria multi-center simulation and which is carrying a material has to include a* ***characteristic color table*** *which corresponds to the material characteristic color table.*

Definition 3.7 *Each ant of the simulation which is carrying some material M_l, has to implement a decision process which gives, as output, a color pheromone template c_j that is used for the material transportation by the ant. This selected color c_j is called* **the ant behavior**.

At each simulation step, a carried material M_l is associated to a color c_j, called the ant behavior in definition 3.7. The ant which is carrying this material will then move by searching in its neighboring position, the one with the highest value of the c_j colored pheromone.

To compute the ant behavior, we search the highest value of the colored pheromone on the space position of the ant and to return the color of this highest value.

The ant moves on the neighboring place which has the highest value of colored pheromone defined by its behavior.

Simulation experiments are made using Repast on OpenMap for a specific following configuration, defined by the initial positions of all the components of the system: (i) the centers, (ii) the queens, (iii) the materials and (iv) the ants. For this experiment, on each center, we put 8 queens, each one is associated to a colored pheromone. On figure 5, we show the result of one simulation where ants progressively aggregate the material around the center, following pheromone trails and clustering algorithm. We can observe the formation of material affectation to each center in order to respect the attraction process, according to the material characteristics.

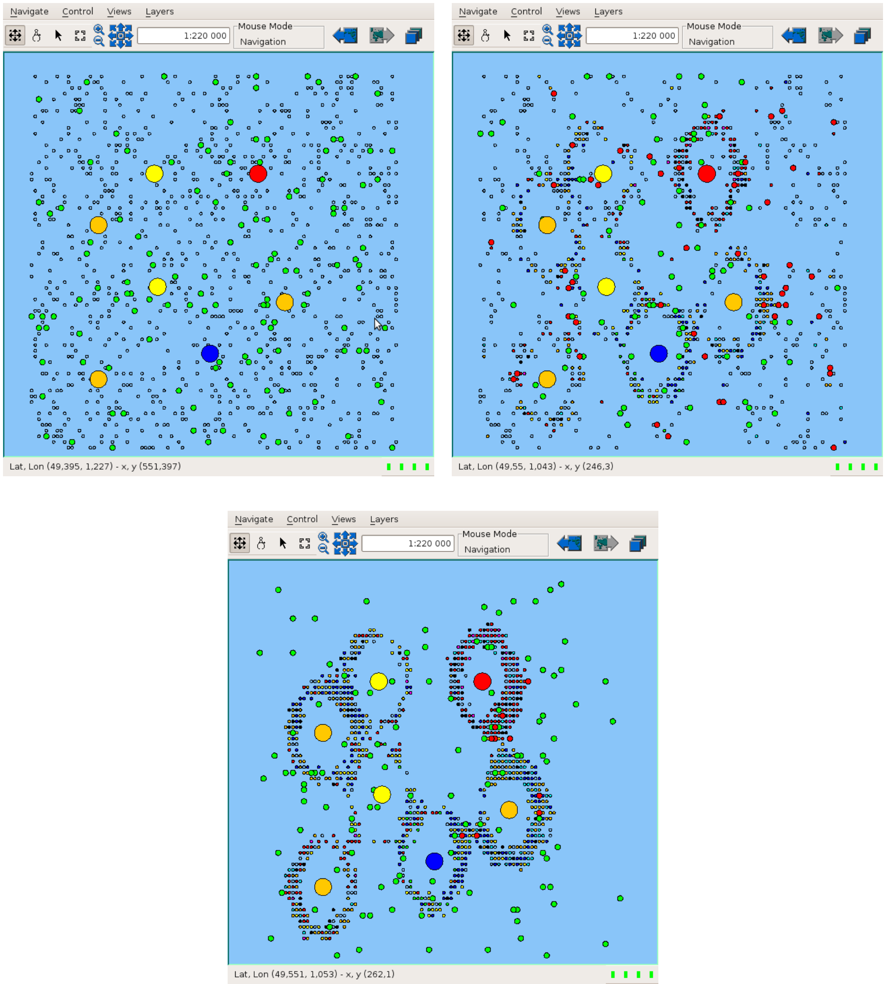


Figure 5 Simulation computation, at the successive steps: iteration 0, iteration 250, iteration 1600.

On figure 6, we make a zoom of the last step of the simulation shown on the figure 5, removing the ant representation. The color of each center corresponds to the colored pheromone of the highest amplitude over the center. The color of each material corresponds to the behavior color of the ant which carries it, according to the definition 3.7.

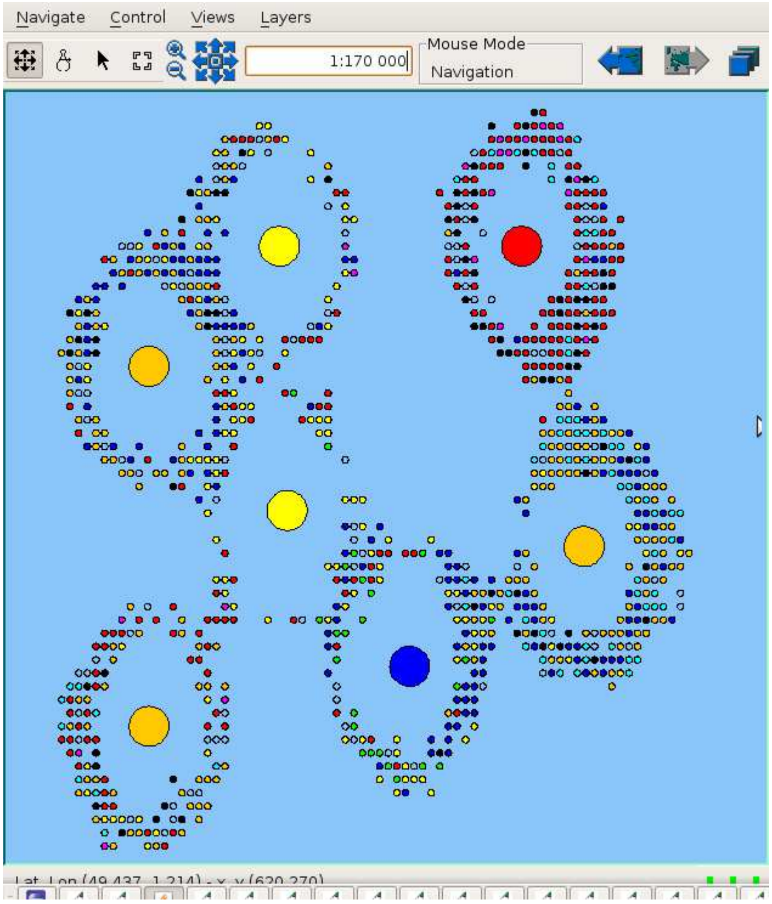


Figure 6 Simulation: zoom on final step

4 Application to Cultural Equipment Dynamics

The multi-template modelling can be used to model cultural equipment dynamics as described in the figure 7. On this figure, we associate to each cultural center (cinema, theatre, ...) a set of queens. Each queen will emit its own pheromone template, associated to a specific criterium (according to age, sex, ...). Initially, we put the material in the residential place. Each material has some characteristics, corresponding to the people living in this residential area. The simulations, corresponding to the previous computations, generate self-organization processes as the results of the set of the attractive effect of all the center and all the templates.

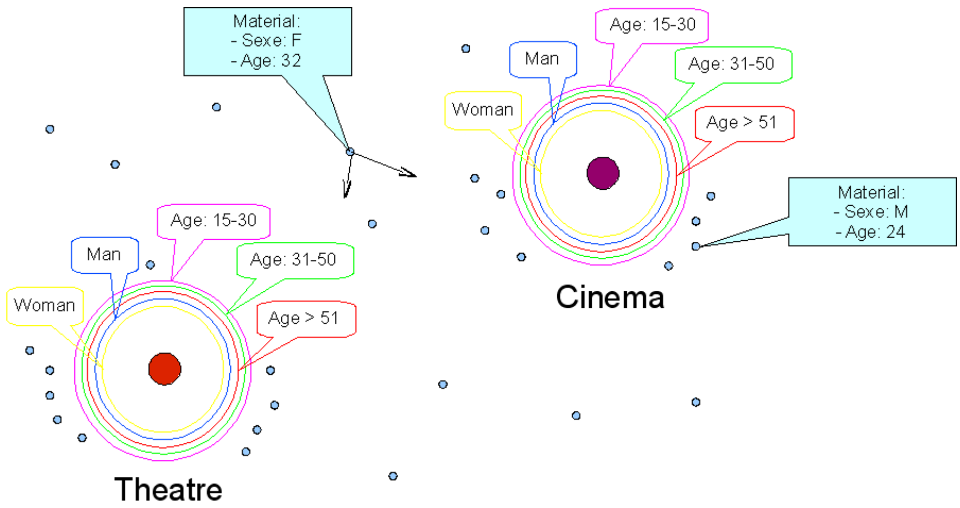


Figure 7 Cultural Equipment Dynamics Modelling

5 Conclusion and Perspectives

Developing dynamical simulations over GIS leading to adaptive and intelligent decision processes is nowadays a great challenge. Urban development and management needs decision making processes which have been developed since many years on deterministic global evolution laws (differential models, for example). The spatial dimension within its complexity is not generally considered in such global model and are often unable to understand some self-organized systems development.

The paper develops some specific swarm intelligence algorithms based on ant colonies processes. Using such decentralized methods, we can model complex multi-center and multi-criteria self-organizations. Urban dynamics can have major benefits by the use of such models in order to simulate and analyze the adaptive usage of urban services like cultural centers. The applicative part of these studies are supported by a French regional project (Haute-Normandie) dealing with the study of cultural dynamics over the urban area of Rouen.

The future steps of this study is (i) to analyze the complexity of the results and to give some interpretation of the distribution generated by the simulation. (ii) to introduce adaptive modeling of the urban centers in respect with their usages. That means how these centers could be able to adapt their own services, according to the users which have been attracted by them, but are also carrying other specificities thanks to the complexity of the multi-criteria involved in the original problem. These futures steps are now in progress and need to augment the behavioral design of the centers. The decentralized approaches which are the characteristics of our models allow such complements in the model, increasing the complexity of the simulation.

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